Research report 136

TEXTURE ANALYSIS AND SYNTHESIS

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The purpose of this report is to present a brief review of the literature on texture analysis, modelling and synthesis, including two very recent investigations of particular interest to the authors, together with a discussion of various attempts by the authors to analyse and synthesize textures which are found in typical videoconferencing images. Some concluding remarks are made about the relative success of these attempts, together with a view toward future work.

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1. Introduction

Texture is an important feature in many images. There has been much research in the many areas relating to the understanding and manipulation of textures. Although there are many accepted terms used to describe textural features, the semantic nature of these terms makes for an inexact description. Two quotes from the literature may serve to present a proper setting for this report.

> "Image texture is a region property or feature of an image that characterizes the structural relationship within the region,"
>
> Faugeras and Pratt [1].

> "Texture is useful in several image processing applications. Changes in texture can be employed to spatially segment an image. Texture measures can be used to classify crops. Finally, texture can be synthesized to 'fill in' regions of an image for purposes of image coding,"
>
> Pratt, Faugeras and Gagalowicz [2].

Although these quotes put the importance of texture in images into perspective, they do not bring us any closer to a proper description of texture. What 'measures' can we use? In order to decide that two neighbouring 'regions' have different textures, what must we know about them? What data do we need to synthesize a texture so that it appears to duplicate the original? This last question implies a fundamental problem : what people see in an image is often related to what they expect to see. There are aspects of textures then which demand that psychology enter into the equation. The scale at which a texture is presented will change the way we describe it. Textures at one scale may be built of different textures at another. There are hierarchies involved. We will consider only the mathematics of the textures, but bear in mind the individual's response to texture.

There are two main approaches to texture (some authors have used three however[3], with the last two as sub-sets of the second approach mentioned here) :

(a) Statistical- global statistics measures such as image moments (mean, variance), correlations between pixels are used to provide a description of the texture. Markov or Autoregressive models may be used to fit the texture.

(b) Structural- the texture is assumed to be formed from the repeated placement over the image of a basic texture building-block known as a 'primitive'. The primitive and the rules for replicating it over the image may in turn be derived from a statistical process of some sort.

Most of the early models of texture fell into the first category. Recently there has been much interest in the second category, with models that are local-area or region-based. In the next two sections each of these approaches will be discussed with reference to the literature.

2. Statistical Texture

In a famous paper, Julesz [4] reported that human subjects were unable to discriminate between synthetic textures with identical first- and second-order statistics but differing higher-order statistics. This conjecture applies in general to textures, but counter examples have disproved it for some textures. Subsequently, Julesz reported that local features in such textures, which he called textons[5], were the key to texture discrimination and that differences in the first-order statistics of such textons was sufficient for discrimination [6]. Until very recently there was little mention of textons in real images. Voorhees and Poggio [7] have reported an algorithm to identify such features and use them to segment real images.

The Julesz conjecture supports the use of autocorrelation functions and spectral densities in texture description, because the autocorrelation function is the expectation of the second-order density function of the texture and the amplitude spectrum is simply the Fourier transform of the autocorrelation. The use of amplitude spectra alone was further supported by Julesz' conjecture that the local positional information concerning each texton is not processed by the visual system, and the phase spectrum is the analogue of position.

Haralick [8] has reported extensively on the use of Gray Level Co-occurrrence Matrices (GLCMs) for texture discrimination and description. The GLCM is used as a histogram of gray-level differences between pixels over the region. The GLCM over the set of vectors distance D apart, $GLCM_D$(i,j) will contain at position (i,j) all those vectors with grey-levels i and j. Typically, the eight nearest neighbours to a pixel are used (D < 2) and grey-levels are quantized into a small number of buckets. Regions of strong texture tend to produce GLCMs oriented toward the diagonal (the outermost of the eight nearest neighbours). Haralick has reported favourable results with such a scheme. GLCMs created over windows in an image have been used for a texture segmentation algorithm [9]. Limited spatial resolution from the windowing hampers the general application of such a scheme.

Faugeras and Pratt [1] have reported a scheme in which the texture is considered to be the result of filtering the output of a random stream of independent, identically distributed random variables. By decorrelating the texture using "whitening" filters, the generating process may be estimated, and hence the filter function. Deguchi and Morishita [10] also considered the use of "time-series" models by using linear estimation to minimize the error between a predicted and actual texture.

3. Structural Texture

Hawkins' view of texture [11] was of the regular or semi-regular placement of a texture 'primitive' over a whole region. This view has perhaps more use in the synthesis of textures than that presented in the previous section. Many researchers have investigated the role of the primitive in texture description, discrimination and synthesis. Zucker [12] presented the idea of an ideal texture, composed of a regularly-spaced primitive over the whole region of interest. Geometric transformations to each placed primitive enable the synthesis of a 'surface texture' to match the real thing. Rosenfeld and his co-workers [13,14] have investigated the ways in which primitives may be extracted, such as thresholding the gray-levels, and to discriminate between them using second-order statistics. Ahuja [15] conceived of texture as a mosaic, each element in the mosaic itself a mosaic and so on down to the level of individual pixels. The hierarchical nature of texture has also been investigated by Burt et al [16], who devised a segmentation scheme based on a pyramid structure. The image to be segmented is represented in the tree at multiple resolutions. An iterative procedure is performed on the tree, with region identity, or class, being passed from father to children down the tree, and a smoothing function modified by this information proceding up the tree, until a convergence criterion is reached. Recently, Spann and Wilson[17,18] have presented hierarchical schemes, using quad-trees, with the advantage of requiring only top-down processing. They also incorporated spatial information with the statistical information, modifying spatial filters by local statistics, and demonstrated superior results.

4. Two Recent Approaches

The work to be presented in this paper is inspired to some extent by two recent investigations. Volet [19] considers textures to be made of a quasi-periodically repeated primitive over the region. His work involved tesselating the region of interest into a number of smaller squares. Within each square an autocorrelation was performed. Median filtering then peak retention enabled the identification of a repeated primitive. In order to take into account the dilation or rotation of the (similar) primitives over the entire region, he used ensembles to create an ideal primitive and used affine transforms [20] to guide the placement of this ideal primitive over the region. The synthesized images he presented were very similar to the originals. Unfortunately, his algorithm required square regions and a large area from which the primitives could be gleaned. In practice, many regions of an image may be polygons, as a result of (texture) segmentation. Their size may make for a poor autocorrelation estimate.

Franke [21] used the amplitude spectrum derived from a windowed, polygonal, textured region and attempted to deconvolve the effect of the window from the spectrum in order to estimate the 'true' spectrum over the extrapolated region. The n highest peaks in the spectrum were then retained and used to reconstruct the texture within the region, with an arbitrary quality. His technique is an iterative process. A forward DFT is followed by the selection of the largest spectral pair not yet found, the inverse DFT then an update of the new texture, and so on until some threshold has been reached. Such a process can lead to favourable results but can also be very time-consuming.

5. Texture in Alvey MMI085

This report forms part of the Warwick University contribution to the collaborative Alvey Project MMI085, "Image Analysis and Coding," which has as its long-term goal the deployment of an efficient algorithm to provide video communications at 64 kbit/s. The emphasis is on so-called second-generation techniques [22], such as image segmentation and region- coding. The aim of the texture study is the provision, at the transmitter, of succinct descriptions of region texture features which may used, at the receiver, to synthesize acceptable approximations to the original regions. It should be noted that there are no algorithms available in the literature which perform such a task well using the structural approach to texture. Given the promise of enormous compression that there is with such a scheme, the pursuit of such seems reasonable. We have briefly investigated the use of autocorrelations and periodograms (amplitude spectra) in texture description and synthesis.

6. Autocorrelation Measures

Volet's approach to identifying primitives with autocorrelations provided good results so use was made of the essence of his algorithm. Unfortunately we were working with regions that were non-rectangular. Many regions in a segmented image are not even convex polygons. The assumption we had to make was that the texture within any region was largely homogeneous so a small part of it could be used as representative of the whole. A square area may therefore be selected and used for the autocorrelation function. There are two autocorrelation estimates that may be used over the square area, known as biased and unbiased estimates. The biased estimator is defined as

$$c_b(k,l) = \frac{\sum_{i=0}^{K-|k|-1} \sum_{j=0}^{L-|l|-1} x(i,j)x(k+i,l+j)}{KL} \tag{1}$$

and the unbiased estimator is defined as

$$c_{ub}(k,l) = \frac{\sum_{i=0}^{K-|k|-1} \sum_{j=0}^{L-|l|-1} x(i,j)x(k+i,l+j)}{(K-|k|)(L-|l|)} , \tag{2}$$

where K and L are the dimensions of the test area. If the area is square, with side N, there are therefore $N^2 \cdot \frac{(N+1)^2}{4}$ multiplications and additions performed to get the result, i.e. O (N^4) operations. The unbiased estimator makes an allowance for the differing number of coefficients in the summation as k and l vary. It is related to the biased estimator by

$$c_{ub}(k,l) = \frac{KL}{(K-|k|)(L-|l|)} \cdot c_b(k,l) . \tag{3}$$

There is support for both estimators in the literature. We investigated the use of both in our work.

In Volet's thesis [19], he performed an autocorrelation over a relatively large area and then performed median filtering to enhance the peaks in the resulting waveform. This technique may be applied if the texture primitive is much smaller than the area over the autocorrelation. In segmented images, unfortunately, the primitive may have dimensions 20 % of the length of a side of the region. It may also be the case that the texture is not visible but none-the-less exists within the region. In view of these factors we decided to first enhance the test area by increasing the contrast, then performing an autocorrelation. The pre-processing step replaces the post-processing filter. Contrast stretching involves three steps.

1. Identify the MAXimum, MINimum and AVErage grey-level pixels.

2. Select the smaller of $\frac{255-\max}{\max-ave}$ and $\frac{\min}{ave-\min}$ as an enhancement factor, F.

3. Add $F \cdot (pixel-ave)$ to each pixel.

The assumptions

$$ave \approx \frac{\max+\min}{2}, ave \approx 128 , \tag{4}$$

should ensure a significant enhancement of contrast.

After median filtering, Volet used the positions of the peaks in the autocorrelation response (there were typically more than thirty around the origin) to select *basis vectors* that describe the local periodicity of the texture primitive. The rules of regular tesselations of polygons (deformations which leave a shape invariant) described by Fejes-Toth [23] were used to identify the shape of the primitive and the rules for local placement.

Unfortunately, due to the small number of peaks obtained with the autocorrelation we used - a result of the relative sizes of the texture primitives we encountered - this technique proved impracticable.

Indications of success with 1-D autocorrelations [24] led to the implementation of a modified scheme. The algorithm for the extraction and placement of the primitive were modified to (see fig. 1)

1. Perform 1-D autocorrelations along every row and down every column.

2. Create histograms of these to identify a rectangle containing the primitive.

3. Use autocorrelations between distant rows and columns to identify the placement vectors.

The third step implies that regular tesselations are not considered with this technique, as the only possible regular tesselation for a rectangular shape results in orthogonal vectors. Figure 2 shows the possible vector pairs. (In effect then, the rectangle is deformed to a parallelogram.) Specifications of obtuse vectors are related to autocorrelations between rows or columns that lead to candidates which have values greater than half the length of the primitive. Note also that using 1-D autocorrelations considerably reduces the computational load as N increases. The number of multiplications and additions is reduced to $2N^2 \cdot \frac{N+1}{2}$, or $O(N^3)$.

Both the biased and unbiased estimator were used initially to test the algorithm. The unbiased estimator performed significantly better, allowing the direct comparison of peaks in the autocorrelation. The progressive reduction in the value of the biased estimator restricts such a comparison. Note however that at long autocorrelation lags the biased estimator tends to produce spurious data.

In order to calculate the placement vectors, rows and columns within the test area, which were as distant as possible but shared very similar autocorrelation coefficients, were cross-correlated and the peaks of these data were used to select the vectors.

The parameters extracted from this autocorrelation technique are

1. The coefficients (length, width) of the rectangle containing the primitive.

2. The coefficients (gradients, offsets) of the vectors specifying the placement rules.

Once these parameters are calculated, the position of every pixel in the region is related to a position in the primitive and is assigned to that value (see fig. 3). The results of applying this technique to real images produce the following observations (for large image regions)

1. The resulting synthetic texture is similar in appearance to the original, BUT

2. The highly regular nature of the texture is displeasing to the eye.

3. There is no variation in local mean across the region, which enhances the 'artificial' appearance of the synthetic texture.

4. Rounding errors in the primitive placement produce jagged boundaries between neighbouring placements of the primitive.

The unpleasant appearance of the highly regular synthetic texture indicates the fact that textures may in general be locally periodic, but are rarely globally periodic, in other words distortions to the local primitive occur over the region. Some method of incorporating these distortions needs to be incorporated into the algorithm to produce a more pleasing structure. A successful scheme should also reduce the jagged effect mentioned in the fourth point. Large differences in local mean can occur within the region. Some method of incorporating this into the algorithm is also desirable.

A solution to the latter problem is fairly straightforward. We chose to use a bilinear interpolation algorithm as a prediction of the pixel values within the region. The averaging of these predictions locally over the region can be used to modify the value supplied from the texture primitive. Consider fig. 4. The aim of the bilinear interpolation scheme for each region is the selection of values for the (unknown) pixels X_0, X_1, X_2 and X_3 that minimize some error function over the region, i.e.

$$\sum_{i,j \varepsilon R} f(x_{i,j}, \hat{x}_{i,j}) \rightarrow 0. \qquad (5)$$

It seemed reasonable to minimize the visible error between each pixel and its prediction. The function $f(x, \hat{x})$ is therefore defined as

$$f(x, \hat{x}) \equiv ABS\left[\frac{x-\hat{x}}{x}\right]. \qquad (6)$$

Turning this function into a form suitable for least-squares minimization (with reference to fig. 4) and taking derivatives with respect to the corner pixels yields the following equations

$$\sum_{i,j \varepsilon R} \frac{d_k(i,j)}{x(i,j)} = \sum_{i,j \varepsilon R} \frac{d_k(i,j) \cdot \hat{x}(i,j)}{x^2(i,j)}, \; k=0,1,2,3. \qquad (7)$$

In matrix form, the left hand side of (7) will be a 1x4 column vector of the summations, the right hand side will be the product of a 4x4 matrix of distance products with a 1x4 vector, the solution for X_k. Inversion of the 4x4 matrix followed by multiplication by the left hand side will provide the solution. The result of applying these equations to image regions was a more pleasing variation in the luminance of the texture across the region, at the expense of four extra bytes of information.

The solution to the former problem is a more formidable challenge. It is the central problem in texture synthesis using placement rules. Volet's solution, once he had identified the local periodicities in each sub-image, was to create, from the ensemble, an ideal sub-image with local periodicities, and to use affine transforms to derive the rules for placement over the texture image as a whole. Affine transforms are linear transforms, such as rotations and scalings, describing point-to-point relationships between given structures. The result is a smooth reconstruction of the texture in agreement with the original.

Unfortunately, our technique provides no ensemble of vectors, only a single primitive and placement rule. The method we investigated for local adaptation involved the identification of the equivalences of the upper left corner of the primitive over the region. From these points, the measurement of the local statistics was used to guide the selection of pixels from the primitive. Note that with a polygonal region, the correspondence may be incomplete. Two deformations of the sub-region are considered.

1. Rotation. If the contents of the primitive correspond to a rotated version of the sub-region concerned, the rotation may be identified by performing correlations between corresponding rows and columns. A linear shift of the peaks in the correlations would indicate a rotation, and this may be used to guide the modified placement rule.

2. Scaling. The correlations between the primitive and a sub-sampled version of the sub-region, or vice-versa, may be used to identify a scaling factor. The difficulty with this approach is that the scaling, if it exists, may not be isotropic.

The results of attempting crude versions of both these deformation analyses were poor. It is recognized that a combination of scaling and rotation is needed in many instances. The jagged effect mentioned earlier is not removed with this technique because the relations between neighbouring sub-regions is not considered. A further discussion will be included in the conclusion.

7. Spectral Analysis

When a region contains a large amount of variation (energy) which is concentrated largely into a small number of spectral points, the retention of these points only may be sufficient to produce a fair approximation to the original. For example, a region of intense stripes may be reconstructed with less than ten spectral values. Consider fig. 5. The original texture is part of the curtain in the "Trevor" image used for video-codec analysis [25]. After an FFT is performed and the magnitude of the coefficients are found, the result is as shown. With the retention of eight spectral peaks (in each half of the Fourier domain) the inverse FFT produces a reliable version of the original. In this case, about 10 % of the original energy in the Fourier domain is retained. In the case of stripes which lie off the main axes, as in fig. 6, the results are still acceptable. The retention of a small number of spectral peaks for each active region are likely to provide a cheap texture descriptor and provide a visually close approximation after reconstruction.

The point we have ignored in the last paragraph is, of course, that the segmented regions are not rectangular. This problem has been considered by Franke in his investigations [20,26-28]. He presents a technique called Selective Deconvolution as a method of 'filling in' (extrapolating) the unknown pixels in a non-rectangular textured region. A few of the spectral lines in the spectrum drawn from this filled region may be retained to reconstruct the original region at the receiver. With reference to a typical textured region, shown in fig. 7, the data $g(i,j)$ can be considered the product of the (unknown) texture over the entire rectangle, $t(i,j)$ with a binary window function $w(i,j)$, i.e.

$$g(i,j) = t(i,j) \cdot w(i,j) . \tag{9}$$

In the Fourier domain the spectrum $G(u,v)$ is therefore the convolution of the spectrum $T(u,v)$ with the spectrum of the window, $W(u,v)$, i.e.

$$G(u,v) = T(u,v) * W(u,v) . \tag{10}$$

Franke's deconvolution scheme involves an iteration. A DFT on $t(i,j)$, set initially to $g(i,j)$, is followed by the selection of the largest spectral pair not yet considered : the position of these lines are used to update a binary filter function which in turn is used to select the best accumulated spectrum which minimizes the error between the known samples, $g(i,j)$ and the inverse transformed spectrum. Following the proper selection, the IDFT completes the deconvolution and the next iteration is performed after extrapolated pixels are assigned. The iteration stops after the region is 'filled-in' to the desired degree. The number of iterations may be large (30 or more) for acceptable results but the technique is proved to converge to a stable solution.

Franke's scheme has obvious drawbacks as a coding technique, as mentioned above, but the fact that a small number of spectral peaks may be used to accurately synthesize texture leads us to consider the following algorithm. Note that this proposal has not been implemented at the time of writing.

8. A Possible Region Filling Technique

The scheme is described pictorially in fig. 8. There are four steps in the process.

1. Perform 1-D autocorrelations along rows and columns using known samples. The most likely period, perhaps using windowed autocorrelations, can be used to extrapolate the data from either end to 'fill in' the corresponding row or column of the rectangle. The extrapolated data can also be made to maintain the second-order statistics of the known samples.

2. Once the rectangle is filled perform a DFT over the rectangle.

3. Select the *n* largest spectral lines from the periodogram.

4. Perform an IDFT (at e.g. the receiver) to approximate the texture signal. The positional information is given from the edge map.

In this way the iteration of Franke's scheme is removed; the desired spectral lines are found from one pass through the DFT-IDFT loop. The potential difficulty with this scheme is obviously that of correlations along short rows or columns. A reliable way around this problem is not immediately obvious.

9. Conclusions and Future Work

We have investigated the description and synthesis of textures, based on a structural model of texture. It is apparent that real textures are often locally-periodic but are rarely globally-periodic. This view is supported by the Julesz conjectures mentioned in the references. The problems with selecting a feature from the centre of an arbitrary region and replicating it regularly over the region mean that it is unlikely to create a pleasing approximation to the original. The incorporation of parameters which lead to smooth deformations to the primitive across the region are therefore highly desirable. The amount of information required with this may limit a coding application.

The ability of a small number of spectral lines to reconstruct most of the gross features of a textured area, as indicated in examples from the text, make the pursuit of a fast and reliable method of extracting such data from a non-rectangular area a worthy one. It is hoped that the development of the algorithm proposed in the previous section will lead to a successful method.

10. Acknowledgements

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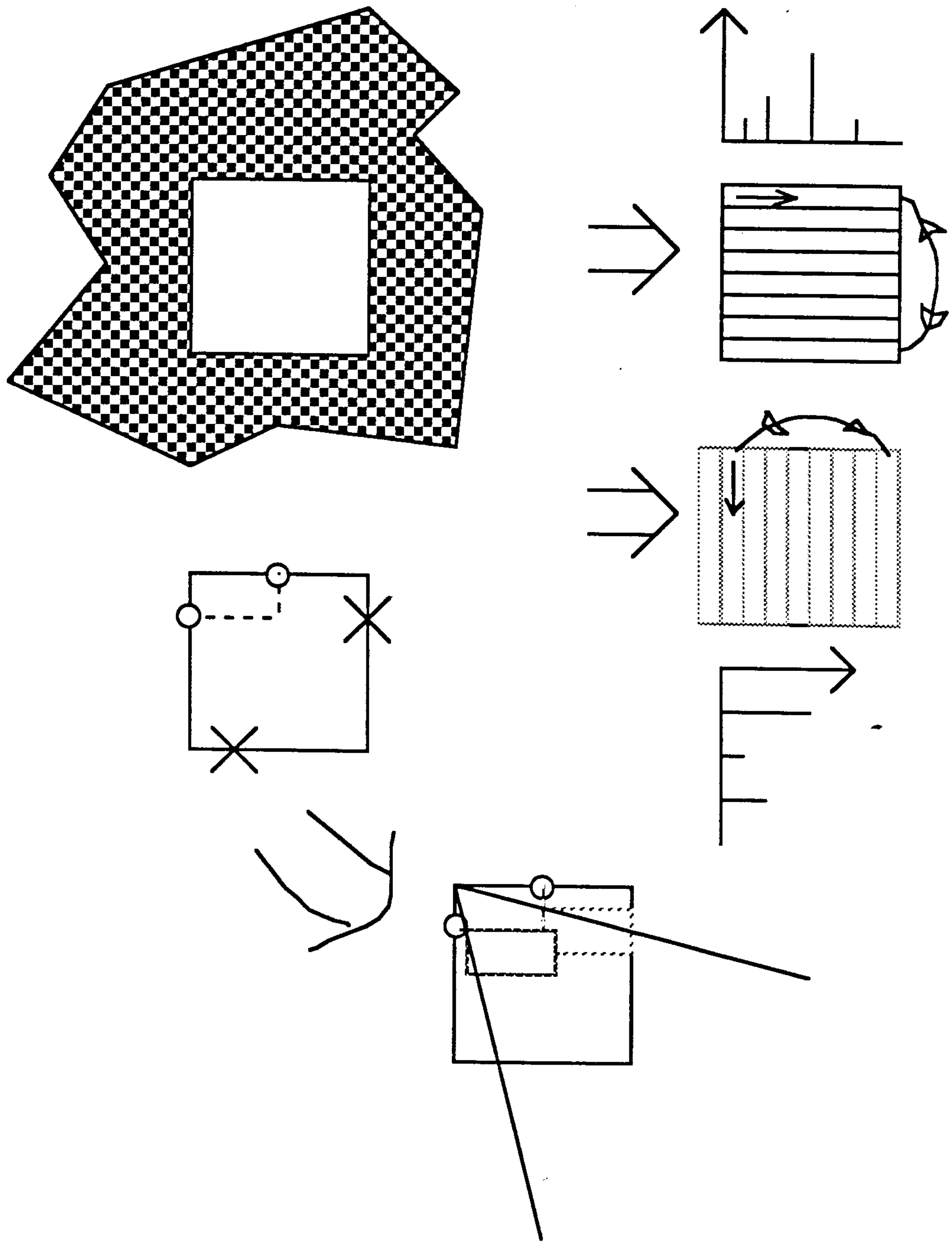


Figure 1. Autocorrelation Scheme.

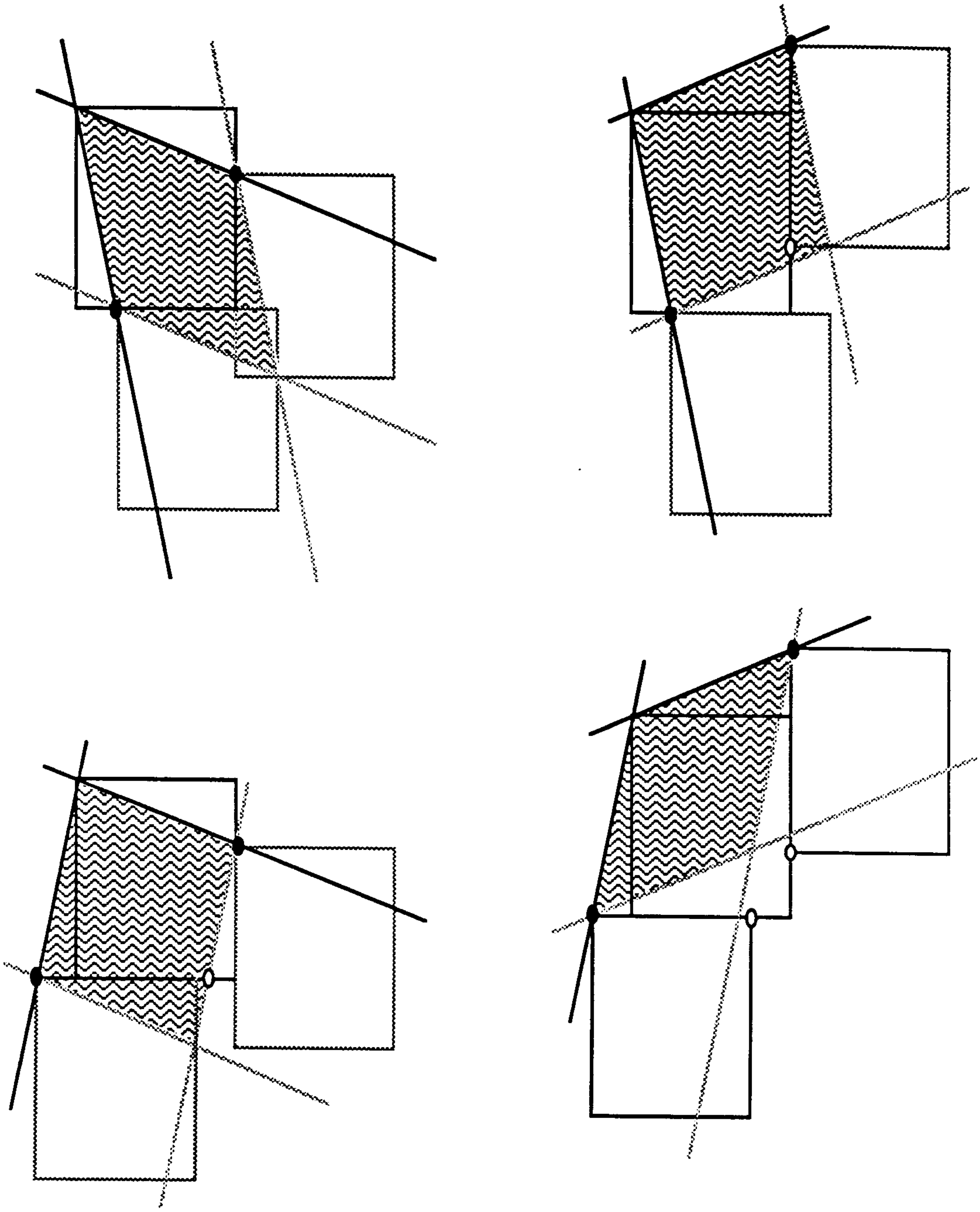


Figure 2. Possible Direction Vectors of Texture.

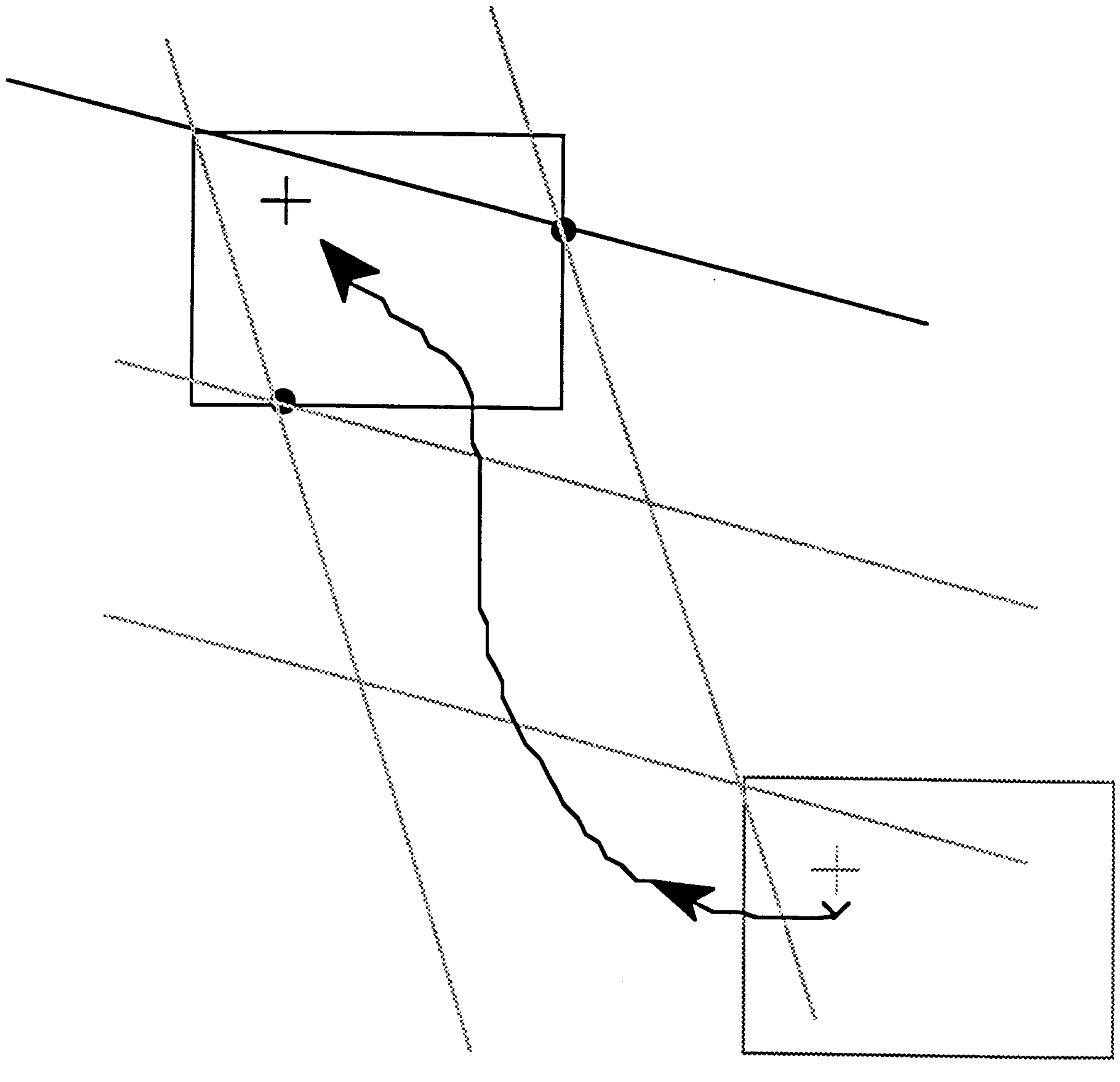
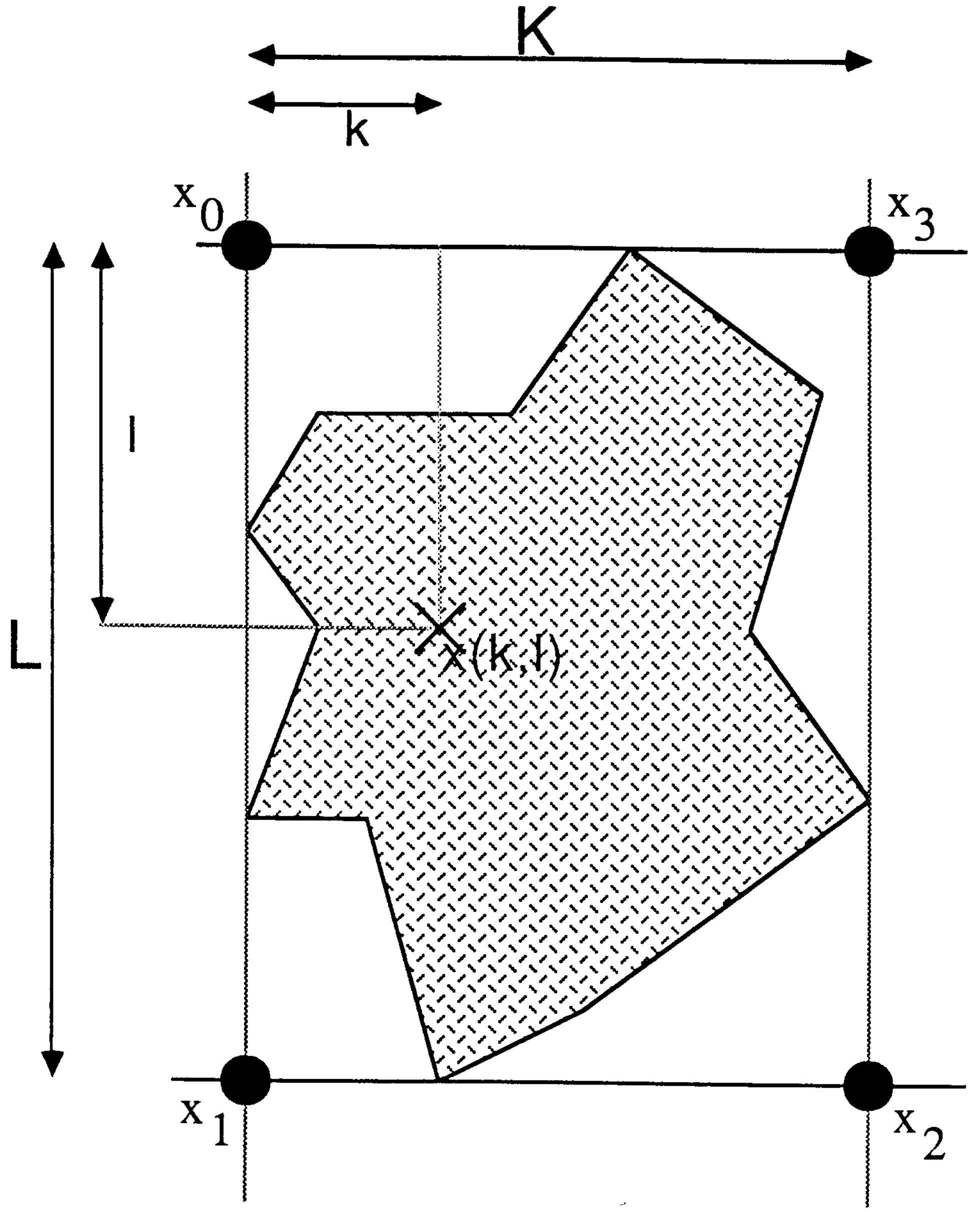


Figure 3. Pixel Placement from Primitive.

$$\hat{x}(k,l) = \sum_{k=0}^{3} d_k \cdot x_k$$



$$\hat{x}(k,l) = \frac{(K-k)(L-l).x_0 + k(L-l).x_1 + kl.x_2 + (K-k)l.x_3}{K.L}$$

Figure 4. Bilinear Interpolation.

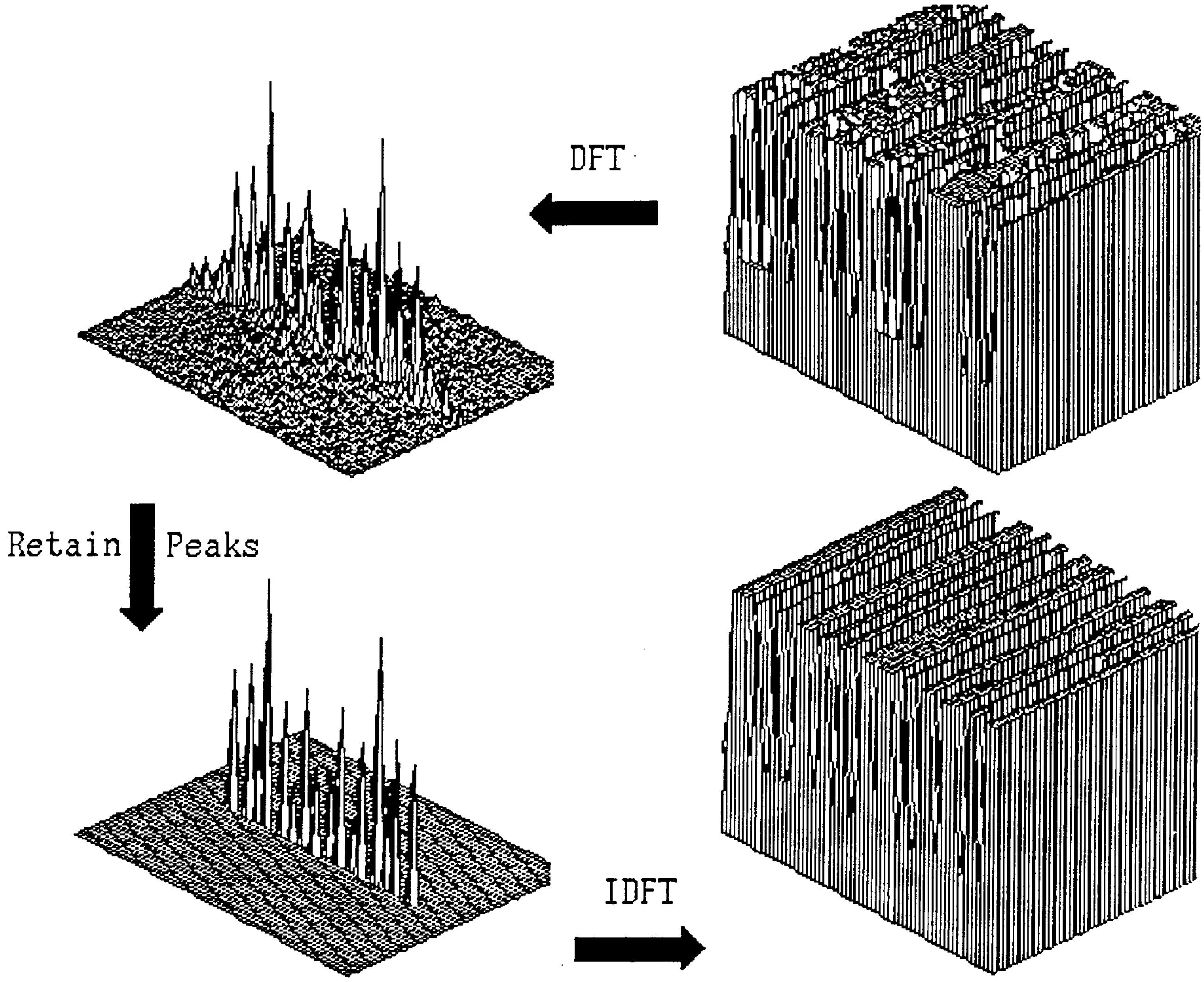


Figure 5. Reconstruction of Vertical Texture.

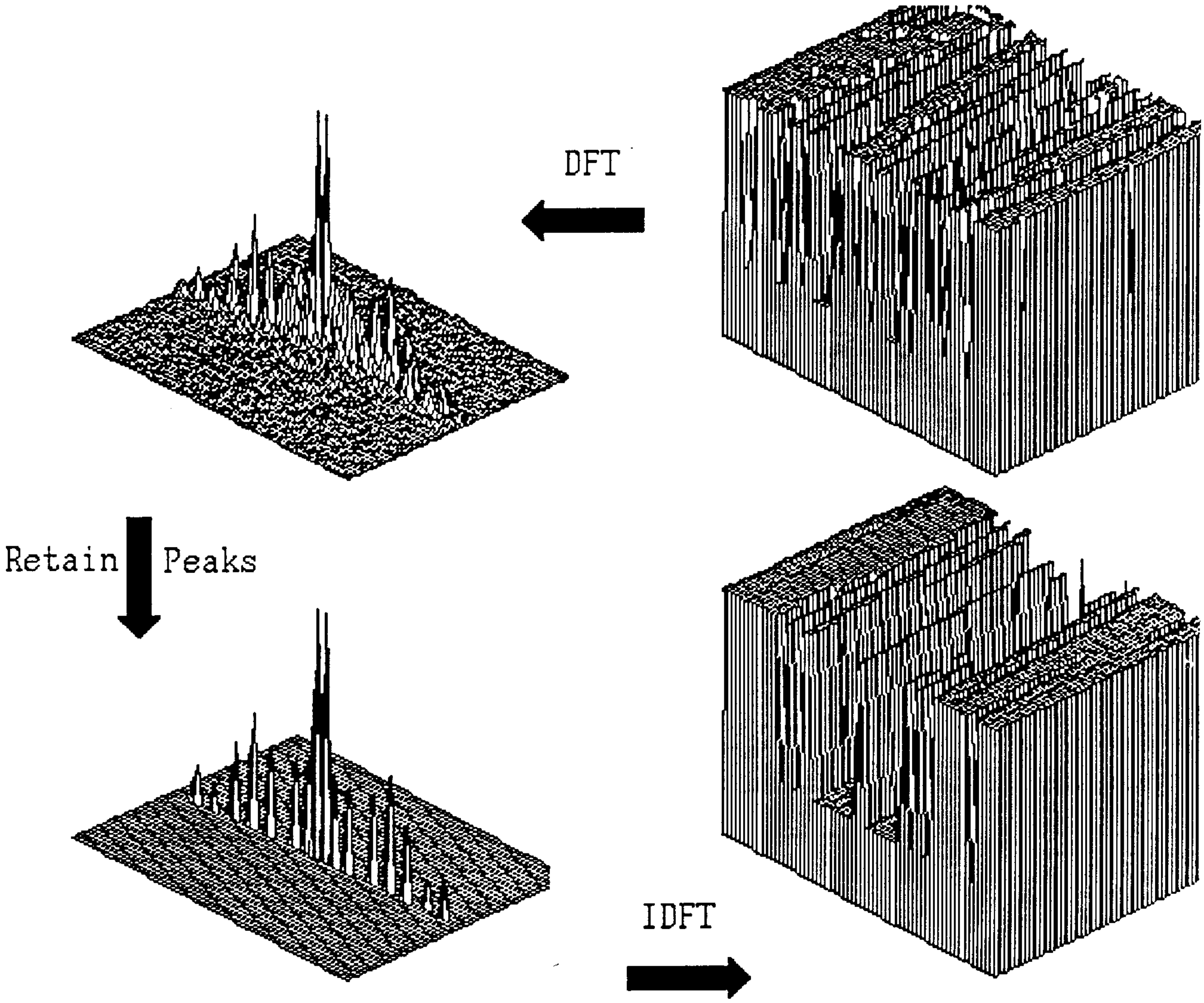
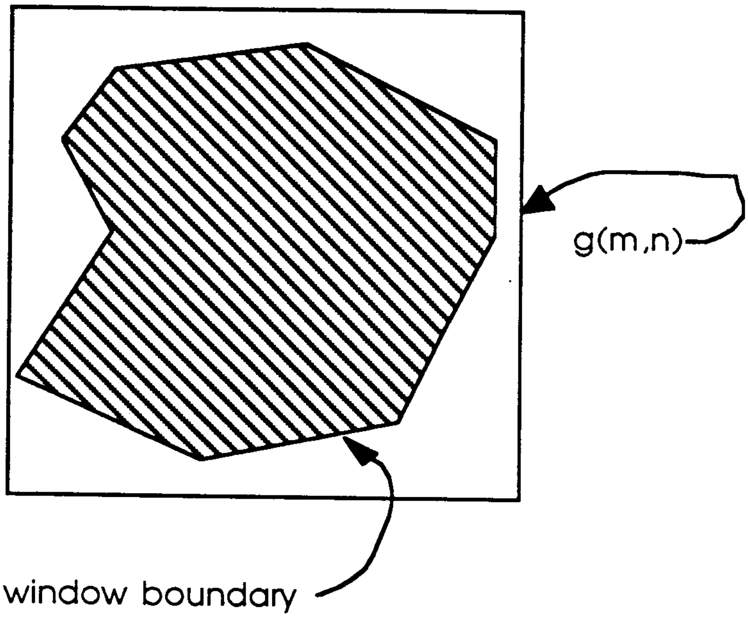


Figure 6. Reconstruction of Angled Texture.



$$g(m,n) = t(m,n) \bullet w(m,n)$$

Figure 7. Textured Region & Rectangle

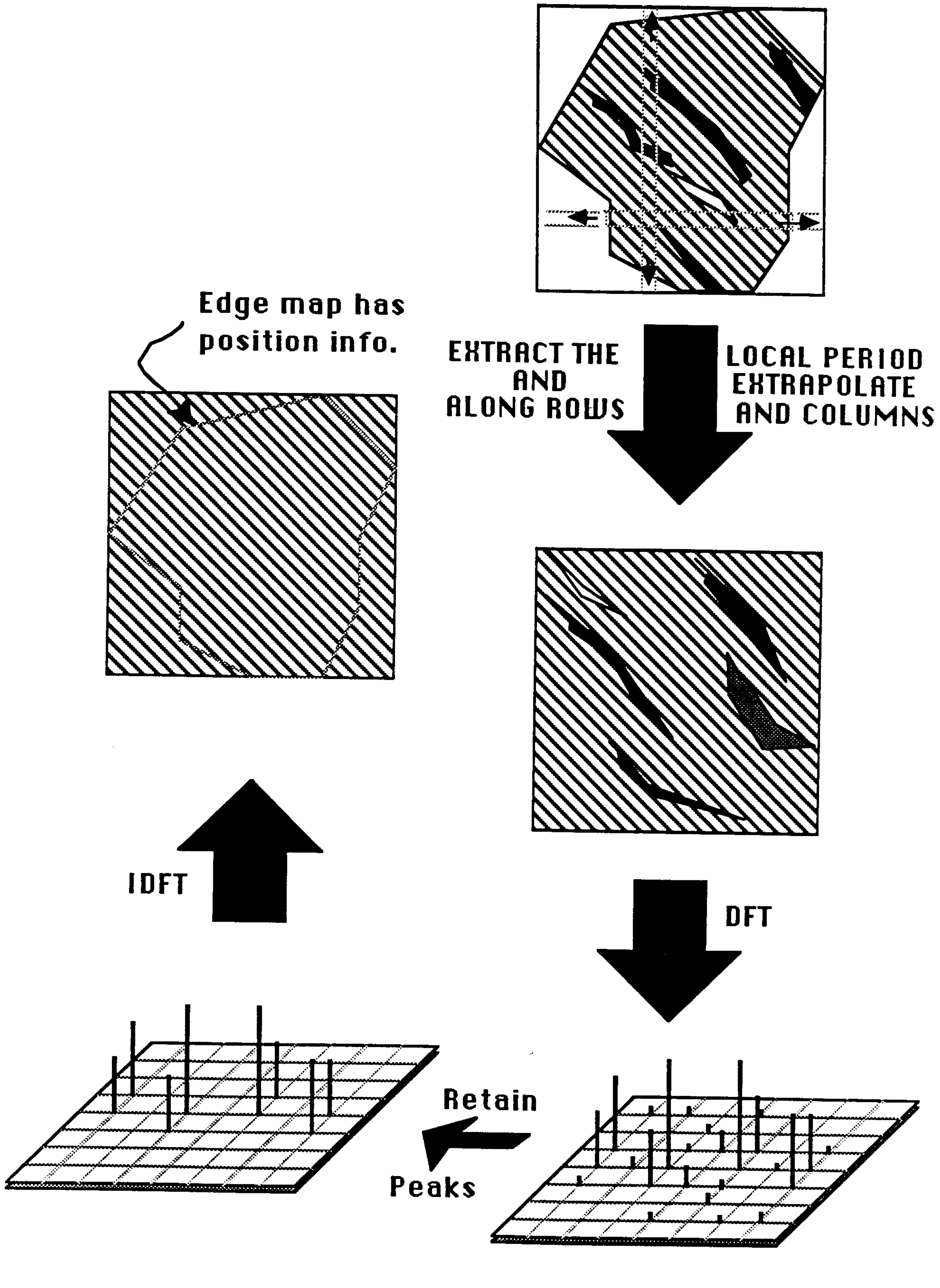


Figure 8. Extrapolation and Selection.